THE USE OF FLIGHT TRACK AND CONVECTIVE WEATHER DENSITIES FOR NATIONAL AIRSPACE SYSTEM EFFICIENCY ANALYSIS

Joseph Post, James Bonn, Mike Bennett, and Dan Howell, The CNA Corp., Alexandria, VA

Dave Knorr, Federal Aviation Administration, Washington, DC

Introduction

Ongoing and proposed studies of the National Airspace System (NAS) are attempting to quantify its performance in order to gauge the impact of new equipment and procedures, and potentially to establish organizational performance goals for the Federal Aviation Administration (FAA). The dynamic nature of the NAS environment, which reflects the continual change in weather and traffic composition, makes comparing different periods of time problematic. New methods to normalize for these effects are needed in order to make more accurate assessments of system performance and facilitate informed decisions.

This paper presents an analytical framework for conducting NAS-wide performance assessments. The proposed approach segments the national airspace into a two-dimensional grid; superimposes flight tracks, flight plans, convective activity, and convective forecasts onto this grid; and then uses statistical techniques to compare these densities. In this manner one can quantify such things as the difference between planned and actual routes, the accuracy of convective forecasts, the impact of severe weather on traffic, etc. The use of two-dimensional statistical techniques borrowed from the fields of image processing and geostatistics can remove much of the arbitrariness involved in previous approaches, which attempt to match similar days.

The first section of the paper describes the specific types of data that may be used to compute density grids, and proposes general methodologies for analyzing these densities. In the next two sections, we present two detailed analyses that illustrate how one might use the density grid concept.

In the first example analysis, we use the densities of lightning strikes and flight plan tracks to generate an estimate of the impact of the severity of convective weather on en route efficiency. From this estimate, we compute a daily index, which can be used to normalize for the effects of varying en route weather. The analysis includes a statistical comparison of the resulting index to various generally accepted indices of NAS-wide delay for 20 days during the spring and summer of 2001. The proposed en route weather index exhibits a significant correlation with these delay indices.

The second example analysis presents a method for quantifying the impact of convective weather on en route efficiency. In this application, we examine the difference between the density of actual flight tracks and planned flight tracks. This difference indicates if and when flights were rerouted. We compare the difference grid to a lightning strike grid by computing the spatial cross correlation of the two matrices. The cross correlation provides a robust and convenient method to relate the changes in flight plans to the convective activity. We then compute a "correlation distance" of the cross correlation matrix, which distills the matrix down to a single value that represents the distance beyond which traffic was not perturbed. By comparing this correlation distance over different time periods, we can get an indication of the effectiveness of traffic flow management initiatives on rerouting aircraft around severe weather.

Flight Track and Convective Weather Density Grids

Typically, the efficiency of national airspace is studied on a flight-by-flight basis by comparing some representation of the "desired" flight trajectory to the actual trajectory. This approach has its merits, but it may not be ideal for studying the impact of adverse weather on traffic, or for analyzing the effectiveness of Traffic Flow

Management (TFM) initiatives. Specifically, there is no indication of enroute traffic congestion or weather in presently available individual flight data sources. We propose an approach based on the time-varying densities of traffic and weather effects.

We begin by superimposing a two-dimensional "rectangular" grid over the airspace of the contiguous 48 states. We typically use a grid size of 0.5 degrees of longitude by 0.5 degrees of latitude, but this size may vary depending on the application. We then compute densities of flight tracks or weather events in those grid cells and compare these densities statistically in order to assess NAS performance.

To date, the following data have been suggested as sources for density computations and related analyses:

- Flight plan tracks
- Actual flight tracks
- Great circle flight tracks
- Wind-optimal flight tracks
- Forecast convection
- Actual convection.

For the analyses presented in this paper, we focused on flight plan tracks, actual flight tracks, and actual convection. We use Enhanced Traffic Management System (ETMS) data to compute flight plan and actual track densities, and cloud-to-ground lightning strike data (as recorded and archived by Vaisala-GAI Inc. [1]) to gauge convective activity.

Flight plan tracks provide an indication of where (and when) traffic desires to go. Depending on the application, we can use either ETMS *FS* messages (scheduled flight plans), *FZ* messages (filed flight plans), or *AF* messages (amended flight plans) [2] to examine the desired path at different times before and during a flight. We use the filed estimated time en route (ETE) and flight plan distance to estimate an average ground speed for the flight. We then generate pseudo-track points for the flight plan route at 1 minute time increments along the proposed route of flight. These pseudo-track points are used to compute flight plan densities.

Actual tracks obviously tell us where the traffic really went. Figure 1 illustrates a sample grid of flight track densities, using a 0.5 degree grid, for a one hour time period.

In the enroute environment, convective weather is the most disruptive to flights. Cloud-to-ground lightning data is an indication of such convective activity. To form densities, we simply count the number of cloud-to-ground strikes during a given time period in a given cell. Figure 2 illustrates a sample lightning strike density grid for a 15 minute period.

In future studies we may wish to use great circle tracks, wind-optimal tracks, or different measures of predicted or actual weather to form densities. By computing a great circle routing or wind-optimal routing between origin and destination airports, we can compute densities of shortest-path or shortest-time routes. Great circle routes are simple to calculate, while wind-optimal routes can be found by using a mathematical model such as OPGEN [3]. We could also use the Collaborative Convective Forecast Product (CCFP) or National Convective Weather Forecast (NCWF) to compute the density of forecast convective activity, and either NEXRAD radar data or lightning strike data to compute actual convective activity density. We used the previously mentioned cloud-to-ground lightning strike data because we found it to be the most convenient.

En Route Weather Severity Index

As a first example illustrating the method of computing densities of flight paths and convective activity, we developed an en route weather severity index. This index may be used to normalize for the effects of convective activity when analyzing the performance of en route airspace. Our index is very similar to the Weather Impacted Traffic Index (WITI) developed at the MITRE Center for Advanced Aviation System Development (CAASD) [4]. The differences between the two indices are discussed later in this section. In the example given below, we computed this index daily on a national level, but it could just as easily be computed locally or for smaller time periods.

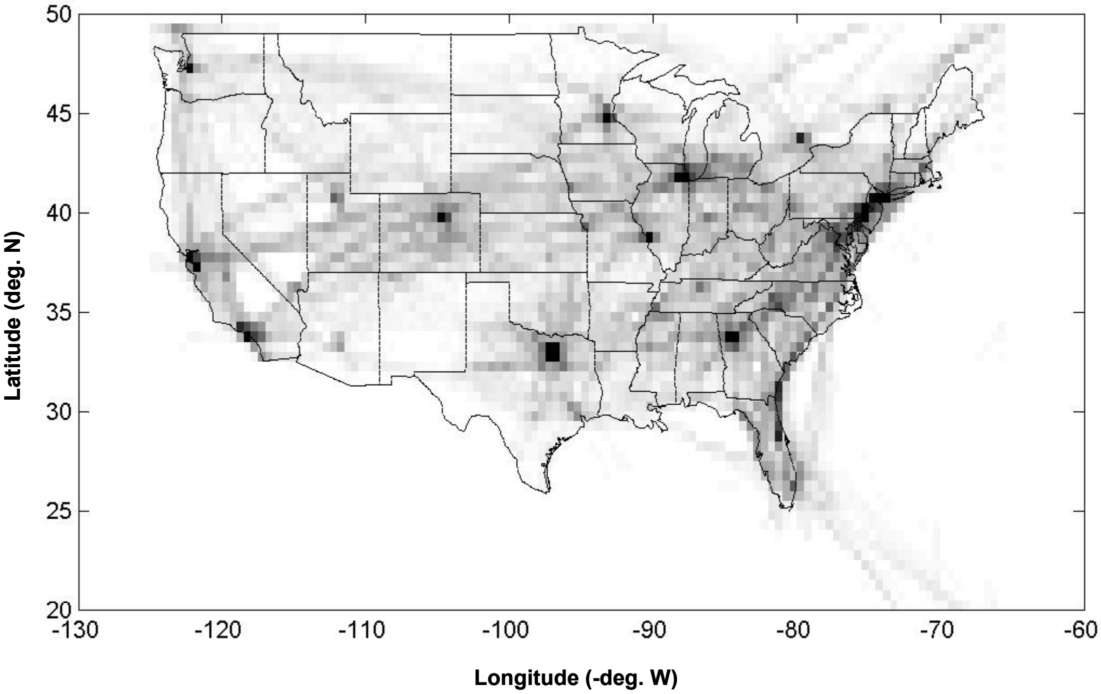


Figure 1. Flight Track Density Example, 0.5 by 0.5 Degree Grid

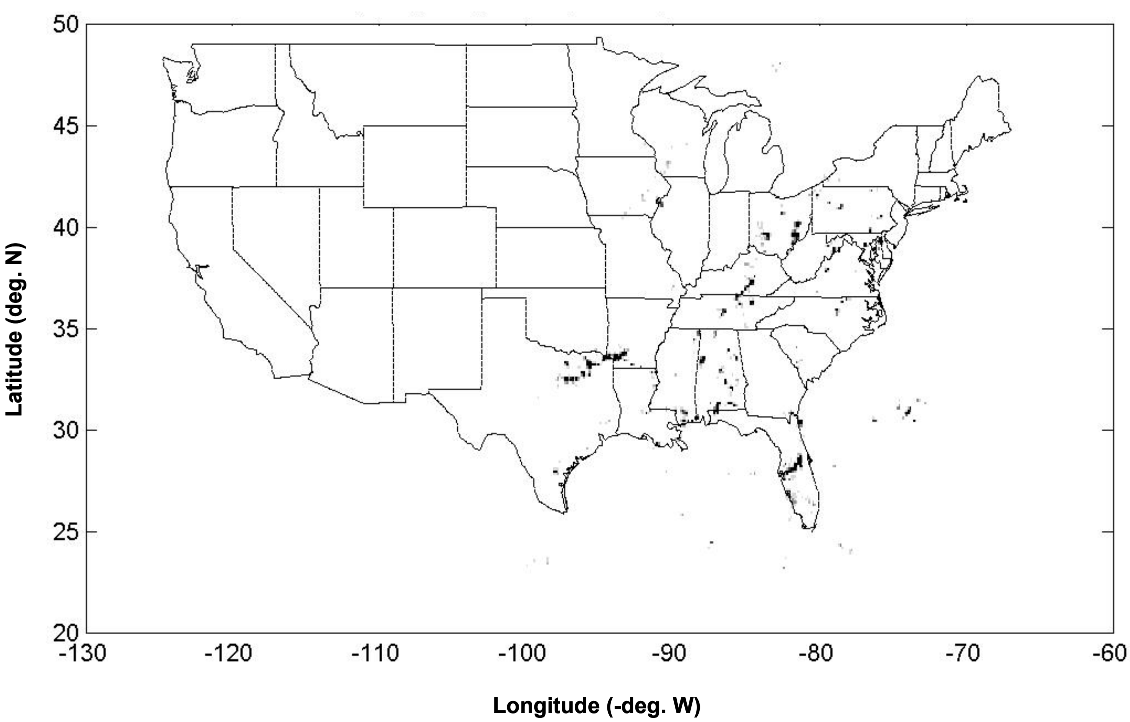


Figure 2. Lightning Strike Density Example, 0.125 by 0.125 Degree Grid

The approach essentially scales cloud-to-ground lightning strike data by the number of flights that *planned* to be in the vicinity of the lightning. Flight plans are used instead of actual tracks, since aircraft will likely have maneuvered or been delayed in order to avoid thunderstorms. Initial flight plans, on the other hand, should reflect where users actually desired to go, given airspace constraints.

To construct this index we partitioned the airspace of the Continental United States (CONUS) into a grid of 0.125 degree by 0.125 degree cells. For each cell, we count the number of lightning strikes in a 15 minute period (see Figure 2). We then estimate the number of aircraft that *planned* to be in each grid cell during the same period of time, using data from ETMS *FS* messages and interpolating as described in the first section. Finally, we take the product of the log of one plus the number of lightning strikes and the number of flight plan points in each grid cell, sum all of the cells for the 15 minute interval, and scale by a constant representing the approximate area of a cell at the equator, i.e.,

$$EWI = \frac{1}{(60 \cdot 1/8)^2} \sum_{t=1}^{96} \sum_{i=1}^{480} \sum_{j=1}^{240} f_{i,j,t} \cdot \ln\left(1 + l_{i,j,t}\right)$$

where

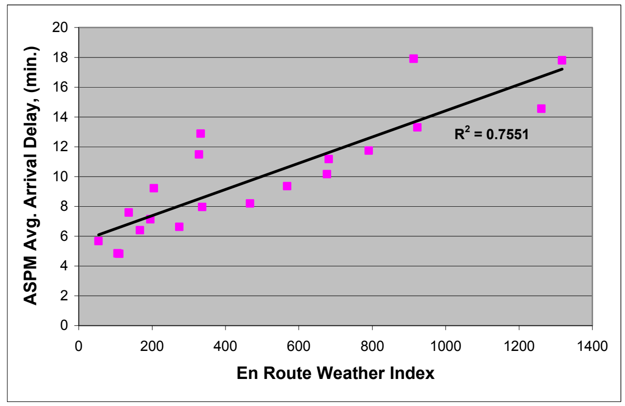
EWI = en route weather index

$f_{i,j,t}$ = flight plan density in cell i,j at time t

$l_{i,j,t}$ = lightning strike density in cell i,j at time t.

The process is then repeated for each 15 minute interval in a day, the values are summed, and an index is obtained that reflects the severity of convective weather relative to the traffic that was planned on that day. The logarithm of the lightning strike density is used to reflect the fact that the number of recorded strikes is nonlinearly related to the severity of convection.

We have calculated this en route weather index for 20 days from the summer of 2001, and compared it to several popular measures of NAS-wide delay. We would expect there to be a strong relationship between the weather index and en route delays. Figure 3 plots the Aviation System Performance Metrics (ASPM) NAS-wide average arrival delay (relative to flight plans)[1] against the en route weather severity index. There is good correlation between this delay metric and the weather index. An ordinary least-squares regression of the weather index on ASPM average arrival delay yields a coefficient of determination (i.e., R^2) of approximately 0.76. Figure 4 plots the ASPM on-time arrival rate for the same days against the en route weather index. Again, the correlation is good, with an R^2 value of 0.72.



Arrival delay computed using flight plan departure times

Figure 3. ASPM Average Arrival Delay vs. En Route Weather Severity Index

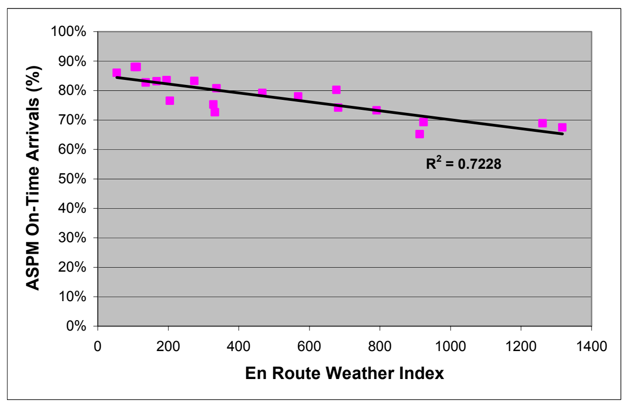


Figure 4. ASPM On-Time Arrival Rate vs. En Route Weather Severity Index

---

[1] ASPM arrival delay relative to flight plan is the difference between actual gate-in time and "flight plan" gate-in time, where the latter is the sum of the flight plan gate-out time and the scheduled block time from the Official Airline Guide [5].

While both our approach and the MITRE WITI place a grid over the CONUS airspace and multiply convective activity by some measure of traffic intensity in each cell of the grid, there are two major differences between the two approaches. First, the WITI uses NCWF severe weather polygons as the source for convective activity. Second, the WITI uses actual flight tracks from a "good weather day" as the data source for traffic. Our approach, on the other hand, uses flight plan traffic for the particular day being analyzed. Our approach has the advantage of being more dynamic, in that day-to-day (and consequently weekly, monthly, and seasonal) changes in traffic are accounted for. Then again, there is some question as to whether the flight plan routes contained in the ETMS *FS* message already take en route weather into account.

Traffic/Convective Weather Spatial Cross Correlation

In the second application of using flight plan and flight track densities, we developed a method for quantifying the impact of convective weather on en route efficiency. In order to make the problem numerically tractable, we group the gridded CONUS airspace cells into overlapping regional partitions that measure approximately 4.4 degrees in longitude by 4.4 degrees in latitude. We start by computing densities for both the planned and actual flight tracks for a given partition. We then calculate the difference between these two matrices, cell by cell, producing a matrix that represents the geographic rerouting of traffic. Next, we compute the spatial cross correlation between this difference matrix and an equivalent partitioning of the cloud-to-ground lightning strike density matrix. The resulting cross correlation matrix is a two-dimensional statistical representation of the impact that en route weather had on the rerouting of traffic for the partition. We calculate the magnitude of this cross correlation as a function of the distance from convection, and, if the partition satisfies a threshold condition, we estimate a "correlation length," which may be thought of as the distance beyond which aircraft are not affected by the convective activity. Finally, we repeat the process for each partition. The resulting correlation lengths can be plotted over a map of the nation to gauge local efficiency, or averaged to provide an indication of the efficiency of rerouting traffic on a national scale. The procedure is described in more detail below, with an example using actual traffic.

Let $L_{i,j}$ be the gridded density of lightning strikes, and $D_{i,j}$ the gridded density of the difference between planned and actual traffic, where $i = -M...M$ and $j = -N...N$. Figure 5 illustrates the difference grid ($D_{i,j}$) for a representative partition over central Florida for the fifteen minute period beginning at 22:00 Coordinated Universal Time (UTC) on 21 June 2001.

In this example the cell size is 0.125 degrees in each spatial direction. Dark areas (positive values) indicate cells where there are more flight plan points than track points. Light areas (negative values) denote cells where there are more track points than flight plan points. Figure 6 shows the gridded lightning strike data for the same spatial grid and time period. In each of these figures the x and y axes represent the change in latitude and longitude, respectively, from the center of the grid, in steps of 0.125 degrees.

Next, we define the two-dimensional cross correlation between the flight plan/track difference matrix and the lightning strike matrix as

$$\chi_{l,m} = \sum_{i=-M}^{M} \sum_{j=-N}^{N} D_{i,j} L_{i-l,j-m}$$

where $l = -M \ldots M$ and $m = -N \ldots N$ [6]. The cross correlation matrix , $\chi_{l,m}$, represents the strength of the relationship between the difference in traffic and the lightning strikes a specified number of grid cells (l in longitude and m in latitude) apart from each other.

The calculation of the cross correlation matrix can be computationally expensive since, for each shift, we must calculate a sum over all of the grid cells being used. As the size of a cell becomes smaller, and thus more cells are needed to capture the same physical piece of geography, it is easy to see that the size of the calculation becomes larger. However, there is a computationally efficient way of calculating correlations, including the two dimensional cross correlation we have described above, using (discrete) Fourier transforms.

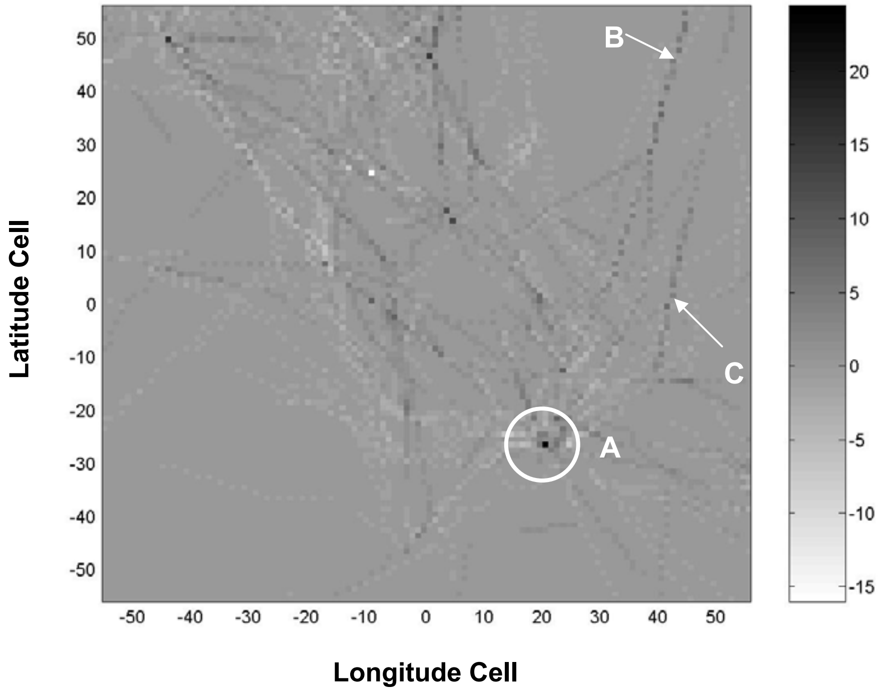


Figure 5. Difference Between Flight Plan and Actual Flight Track Densities, 0.125º x 0.125º Grid

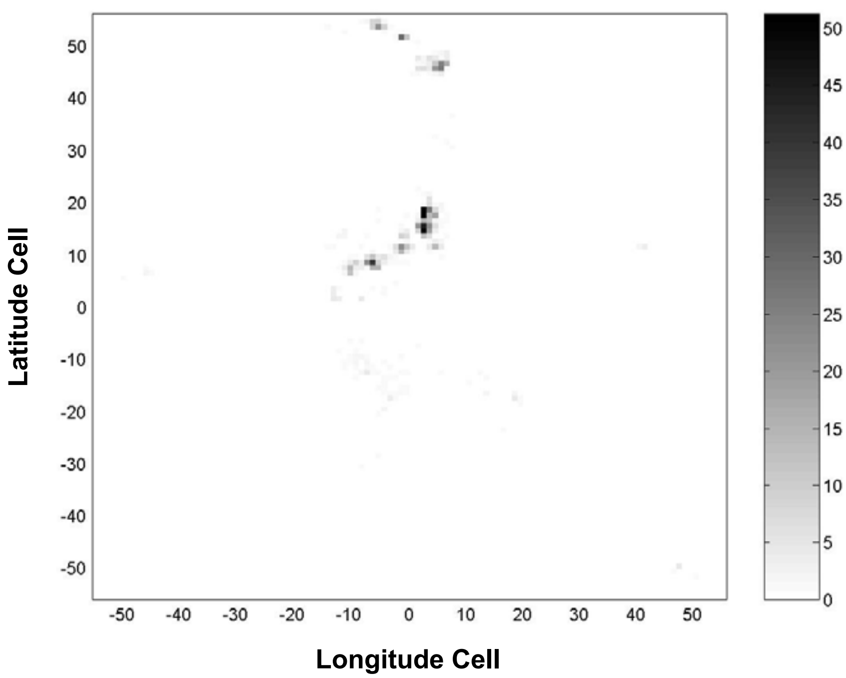


Figure 6. Lightning Strike Density, 0.125º x 0.125º Grid

The two-dimensional discrete Fourier transform for an M by N matrix f is defined as

$$F(u,v) = \frac{1}{MN} \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} f(m,n) e^{-2\pi i \left(\frac{mu}{M} + \frac{nv}{N} \right)}$$

for $u = 0 \ldots M-1$, $v = 0 \ldots N-1$. Here m and n represent position in the x and y (or longitude and latitude) directions, respectively, while u and v represent spatial frequencies in these directions. The inverse discrete Fourier transform is given by

$$f(m,n) = \sum_{u=0}^{M-1} \sum_{v=0}^{N-1} F(u,v) e^{2\pi i \left(\frac{mu}{M} + \frac{nv}{N} \right)}$$

for $m = 0 \ldots M-1$, $n = 0 \ldots N-1$. In fact, the correlation between two functions is related to the convolution of those functions. For the above cross correlation, we can compute the entire cross correlation matrix, for all shifts, with the one calculation

$$\chi = IFFT\{FFT(D) \cdot FFT^*(L)\}$$

where FFT represents the Fast Fourier Transform function, $IFFT$ the Inverse Fast Fourier Transform function, and *FFT*(L)* represents the complex conjugate of *FFT(L)* [7]. For this calculation to be accurate, we must pad each of the discrete functions D and L by zeros as an anti-aliasing technique. That is, for each function, the size of the discrete grid of data points that is input into the FFT is $2(2M+1) \times 2(2N+1)$; however, all except the first $(2M+1) \times (2N+1)$ positions are zero. That allows the consideration that the data is periodic in both spatial dimensions without changing the form of the cross correlation grid.

Figure 7 shows an example of the cross correlation matrix formed from the two data sets used in Figures 5 and 6. In Figure 7, the x and y axes represent the shifts (l and m) in longitude and latitude cells for finding the cross correlation value. The figure quantifies, spatially, the impact that the weather of Figure 6 had on the traffic of Figure 5. For example, in Figure 5 one can see a dark area approximately 20 cells east and 25 cells south of the origin (represented as Area A), corresponding to a surplus of flight plans over actual traffic. In Figure 6, the principal convection is about 15 cells north of the origin. Thus traffic was rerouted from an area about 20 cells east and 40 cells south of the main convective area. This can be seen as Area A in Figure 7, which represents this shift of traffic *relative to the convection*. One can also see routes in Figure 5 (indicated by B and C) that apparently were not used, or were used less than had been planned. Equivalent structures are present in the cross correlation matrix, and indicate the position of these unused routes relative to the convection in the partition.

We would like to distill the structures of the correlation matrix of Figure 7 into a single metric that captures in some sense the "average distance" that traffic was rerouted, and hence the efficiency of the rerouting. There are various ways in which to construct such a metric from the cross correlation matrix, and we present one example here. We propose a "correlation length," derived from the magnitude of the cross correlation of Figure 7 as a function of the distance from the origin. For numerical reasons, we are unable to compute this correlation length for partitions with little activity. Where there are sufficient weather-related difficulties, or large amounts of lightning, we expect the un-shifted position in the cross correlation function, $\chi_{0,0}$, to be large. That is, there should be a sufficiently large relationship between the difference in the planned and actual traffic and the number of lightning strikes in the un-shifted partition. Therefore, we only compute a correlation length when $\chi_{0,0} > \delta$, for some given threshold value, δ. For example, when using data binned into one minute spatial grids in latitude and longitude, we used a threshold value of $\delta = 56$. For larger grids, the threshold value is increased proportionally to the area of a typical cell.

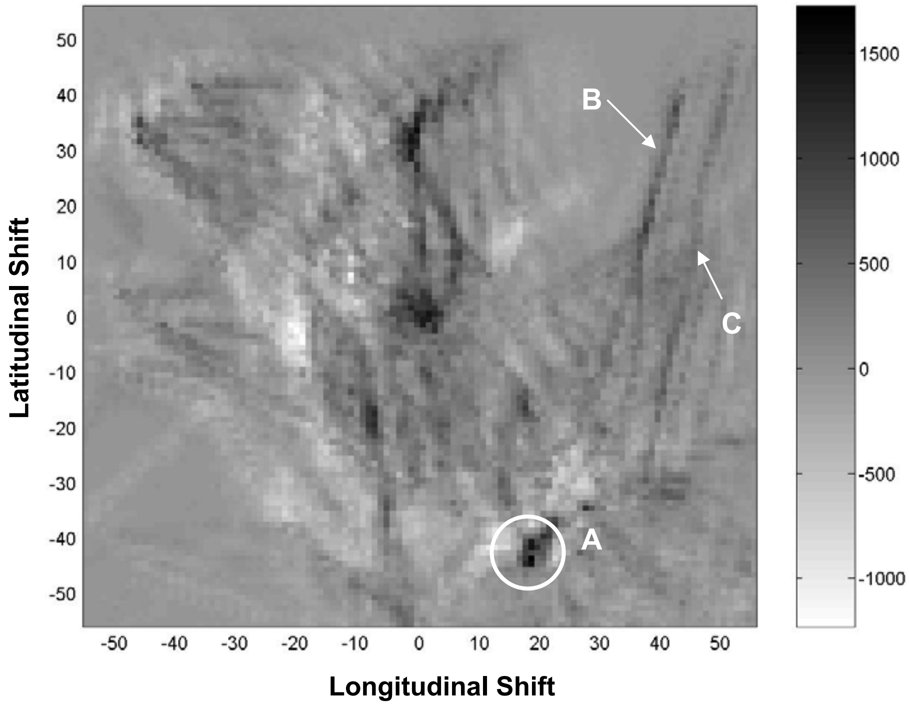


Figure 7. Cross Correlation of Flight Track/Plan Difference Matrix (Figure 5) and Lightning Strike Matrix (Figure 6)

To find the correlation length for a partition that satisfies the criterion described above, we first average the cross correlation grid over the finite number of discrete distances that are represented by the various shifts in the grid. That is, we define a function $corr(d)$ as

$$corr(0) = \chi_{0,0}$$

$$corr(1) = \frac{\chi_{1,0} + \chi_{0,1} + \chi_{-1,0} + \chi_{0,-1}}{4}$$

$$corr(\sqrt{2}) = \frac{\chi_{1,1} + \chi_{1,-1} + \chi_{-1,1} + \chi_{-1,-1}}{4}$$

and so on. We then fit this discrete function (using least squares) to the continuous curve

$$f(x) = ae^{bx} + c$$

with free parameters a, b and c. Once this fit is made, we define the correlation length to be λ where $f(\lambda) = \frac{1}{e} f(0)$. In other words, we find lambda by solving

$$ae^{b\lambda} + c = \frac{a+c}{e}.$$

Figure 8 illustrates how λ is obtained for a particular partition. The "noisy" curve is the average of the cross correlation matrix values at discrete distances, $corr(d)$. The (shifted) exponential function that has been fitted to $corr(d)$ is also shown. Additionally, Figure 8 shows the computed correlation length ($\lambda = 15.4$ nautical miles) and the corresponding decrease in the correlation function, illustrating how the correlations drastically decrease as one moves further away from high-density lightning strike areas.

Figure 8 addresses only one partition, that centered at 27.5 degrees latitude and -81.5 degrees longitude, using one minute spatial cells. Figure 9 presents a histogram of the correlation lengths seen over the entire nation (for those partitions that exceed the threshold). The mean correlation length is 16.1 nautical miles.

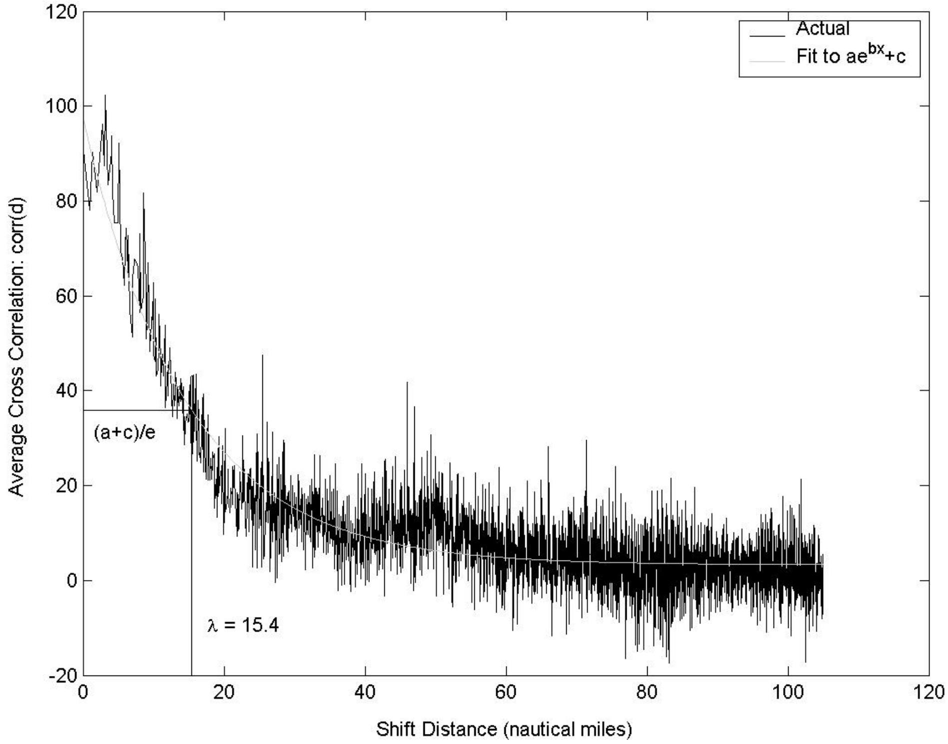


Figure 8. Cross Correlation of Flight Track/Plan Difference and Lightning Strike Grids as a Function of Shift Distance, and Associated Exponential Fit

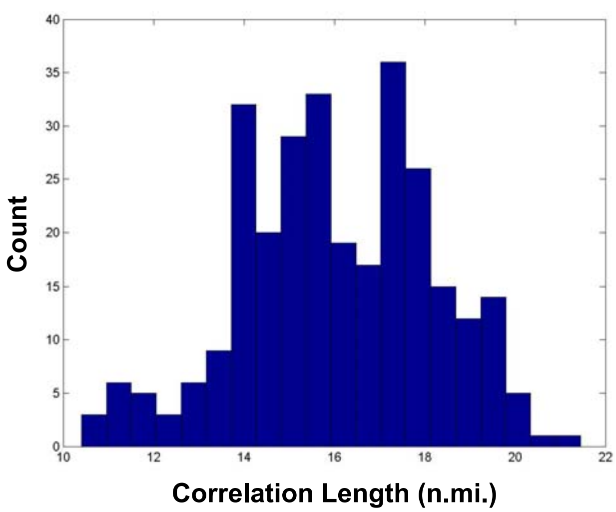


Figure 9. Correlation Length Distribution, 21 June 2001, 22:00-22:15 UTC

The correlation lengths thus described and displayed in Figures 8 and 9 represent the distance beyond which aircraft are not significantly impacted by convective activity, on average. The correlation length is scale invariant, meaning that a linear scaling of the lightning strike density or the flight plan/track difference density would not affect the statistic.[2] This may or may not be a desirable characteristic for a NAS efficiency metric, depending on the ultimate objective of the analysis. Further research could be conducted to develop an equivalent statistic that is sensitive to the magnitude of the lightning strike matrix, and would therefore produce equivalent results for small reroutings around weak convection and large reroutings around strong convection.

[2] Since the zero-shift correlation value must satisfy a threshold criterion in the current formulation, a linear scaling could in fact affect the correlation length. By resetting the threshold as a function of the mean value of the product of the two matrices this problem would be avoided.

Conclusions

In this paper we have demonstrated how aircraft track, flight plan, and convective activity densities can be calculated using ETMS and lightning-strike data. The techniques of spatial statistics can then be used to systematically analyze these densities in order to quantify NAS performance, without the arbitrariness inherent in other approaches that attempt to identify "equivalent days." Some of the techniques proposed are computationally intensive, and, given current technologies, would not be suitable for daily calculation.

We have presented two examples of such analyses in this paper. In the first, we used densities of flight plan tracks and lightning strikes to construct an en route weather index, which provides an indication of the severity of weather relative to traffic patterns. This en route weather index correlated very well with various NAS-wide delay indices, suggesting that it is a good indicator of weather severity. In the second example, we used flight plan, actual track, and lightning strike densities to compute the cross correlation between convection and the flight plan/track difference. This cross correlation captures the impact of convective activity on flight trajectories. Various metrics may be calculated from the resulting cross correlation matrix. In the example, we proposed a "correlation distance" that reflects the distance beyond which convection has little impact on flights.

A specific application of the cross correlation technique presented here might be to assess the effectiveness of FAA Traffic Flow Management (TFM) initiatives. For example, as part of the Collaborative Decision Making (CDM) effort, the Collaborative Routing Coordination Tools (CRCT) are being developed by the FAA's Free Flight Program Office and MITRE/CAASD. CRCT is intended to aid en route traffic managers with rerouting traffic around flow-constrained areas, such as those surrounding thunderstorms [8]. Correlation techniques similar to those described here could be used to assess the effectiveness of CRCT. The correlation distance presented here could be modified to reflect the distance aircraft were rerouted (or delayed) per "unit" of convection. One could then test to see if this metric had decreased for a given facility (or nationally) following CRCT introduction.

References

[1] Cummins, Kenneth L., E. Phillip Krider, and Mark D. Malone, Nov. 1998, "The U.S. National Lightning Detection Network and Applications of Cloud-to-Ground Lightning Data by Electric Power Utilities," *IEEE Transactions on Electromagnetic Compatibility*, Vol. 40 No. 4, pp. 465-480.

[2] Volpe National Transportation Systems Center, June 2002, "Enhanced Traffic Management System (ETMS) Functional Description," Version 7.4, VNTSC-DTS56-TMS-002, Cambridge, MA.

[3] CSSI Inc., "OPGEN-RING User Manual, Issue 1.0," Washington, DC.

[4] Callaham, Michael B., *et al.*, 2001, "Assessing NAS Performance: Normalizing for the Effects of Weather," *4th USA/Europe Air Traffic Management R&D Symposium*, Santa Fe, NM.

[5] FAA Office of Aviation Policy and Plans, May 2002, "Documentation for the Aviation System Performance Metrics (ASPM) Actual versus Scheduled Metrics," Washington, DC.

[6] Rosenfeld, Azriel, and Avinash Kak, 1982, *Digital Picture Processing*, Orlando, FL, Academic Press.

[7] Press, William H., *et al.*, 1992, *Numerical Recipes in C: The Art of Scientific Computing*, Cambridge, UK, Cambridge University Press, pp. 496-500.

[8] FAA Free Flight Program Office, June 2002, "Investment Analysis Study Report: The Business Case for Free Flight Phase 2," Washington, DC.